An Unsupervised Pattern Recognition Approach for AE Data Originating from Fatigue Tests on Polymer-Composite Materials

Dinh Dong Doan, Emmanuel Ramasso, Vincent Placet, Lamine Boubakar, Noureddine Zerhouni

7th European Workshop on Structural Health Monitoring
July 8-11, 2014. La Cité, Nantes, France

An unsupervised pattern recognition approach for AE data originating from fatigue tests on polymer-composite materials

Dinh Dong Doan[1], **Emmanuel Ramasso**[1,2], **Vincent Placet**[2], **Lamine Boubakar**[2], **Noureddine Zerhouni**[1]

[1] *AS2M, FEMTO-ST, 32 avenue de l'Observatoire, 25000 Besanon*
[2] *MEC'APPLI, FEMTO-ST, 32 avenue de l'Observatoire, 25000 Besanon*

dinhdong.doan@femto-st.fr

ABSTRACT

Acoustic Emission (AE) technique is gaining more and more interest for structural health monitoring (SHM) in polymer-composite materials. Recent literature has shown that using appropriate pattern recognition techniques (PRT), the identification of the natural clusters of acoustic emission data can be obtained. This work investigates acoustic emission generated during tension fatigue tests carried out on a carbon fiber reinforced polymer (CFRP) composite specimen. Since fatigue data processing, especially noise reduction remains an important challenge in AE data analysis, a noise modeling has been proposed in the present work to tackle this problem. A Davies-Bouldin-index-based progressive feature selection has been implemented to reduce high dimensional fatigue dataset. A classifier offline-learned from quasi-static data is then used to classify the processed data to different AE sources. An adaptation has been studied to enable the classifier to generate new class, i.e. AE source, for unidentified AE events. With efficient proposed noise removal and automatic separation of AE events, the results of this work provide an insight into fatigue damage development in composites and then ability to health assessment which is necessary for residual life prediction.

KEYWORDS : *organic-matrix composites, acoustic emission, data clustering, noise reduction, feature selection.*

INTRODUCTION

AE testing has become a recognized nondestructive test (NDT) method, commonly used to detect and locate faults in mechanically loaded structures and components. AE could provide comprehensive information on the origination of a discontinuity (flaw) in a stressed component and also provide information pertaining to the development of this flaw as the component is subjected to continuous or repetitive stress [1, 2]. Moreover, the method has been developed and applied in numerous structural components, such as steam pipes and pressure vessels, and in the research areas of rocks, composite materials, and metals.

Acoustic emissions (AE) are the stress waves produced by the sudden internal stress redistribution of the materials caused by the changes in the internal structure. Possible causes of the internal-structure changes are crack initiation and growth, crack opening and closure, dislocation movement, twinning, and phase transformation in monolithic materials and fiber breakage and fiber-matrix debonding in composites. Most of the sources of AE are damage-related; thus, the detection and monitoring of these emissions are commonly used to predict material failure.

With a huge noisy amount of data originating from fatigue loading tests, a major challenge in the use of AE technique is to associate each signal to a specific AE source related to noise or a damage mechanism. This analysis is a non-trivial task for two main reasons. First, AE signals are complex objects that must be characterized by multiple relevant features. Second, there is no *a priori* knowledge of the acoustic signatures of damage events and these are assumed rather scattered.

In the literature, dealing with the challenge of big data due to high sensitivity of AE sensors and to long-term fatigue loading experiments, several processing approaches have been proposed by [3–6]. In [3, 4], it is considered that only signals with amplitude higher than 70 dB or recorded above 80% of peak load contain information related to damage mechanisms. This filtering is subjectively supposed to be efficient in terms of quantitative reduction but it could take a serious risk at missing low and medium energy AE sources that condition the onset of more severe damage mode. In [5], "friction emission" tests in which the maximum cyclic load was decreased to a level that was insufficient to generate crack growth were performed to understand the AE signal characteristics arising from hydraulics, machine start and stop, slippage, grating between fracture surfaces (also referred to as "fretting"), and abrasion of load train. All of the AE events at this lower peak load were therefore assumed to be due to friction emission. Emission having the characteristics of friction emission was then filtered. Friction emission testing was useful and did provide reference waveforms to aid in the differentiation of noise from cracking. However, it did not provide all-inclusive reference parameters for data filtering. This is because the loads were lower than those in the formal fatigue tests. Besides, this specialized kind of test requires a specific load level mentioned above that is not always easily determined. A more complex denoising process developed by [6] that combines PCA and K-means and several validation techniques was presented to be able to classify more than 60% of the detected signals as noise, before the application of a SOM algorithm to separate AE events from the residual noise in the remaining dataset recorded during long time corrosion monitoring of a pre-damaged post tensioned concrete beam.

High dimensional feature space reduction is a remaining challenge to statistical processing and classification of AE data. In the literature, many approaches for AE data processing [1, 2, 7] are conditioned by Principal Component Analysis (PCA). The latter provides a feature space reduction as well as extraction of relevant components subset from the original features set. This algorithm assumes that 1) the linear combination of features improves the relevancy of the principal components and 2) a large variance implies meaningfulness. Other approaches [8–10] rely on a specific subset of features such as energy, rise time, duration, amplitude [8] or reduce feature dimension space by using complete link hierarchical clustering in order to merge the correlated features into groups [9]. Those apply a greedy approach that generates all possible feature combinations and then selects the one which optimizes a given criterion [10, 11]. The goal of the criterion is generally to evaluate the quality of the partition provided by the clustering. Most of criteria are based on the Euclidean distance to assess the membership of an AE hit to a given cluster. Thus the applicability of this approach is limited to clustering algorithms which are based on the Euclidean distance. The PCA and K-means are theoretically related to each other as shown in [12]. The main reason to account for the performance of this couple is actually due to the link between both tools. An alternative approach based on the Gustafson-Kessel algorithm (GK) [13] was proposed in [14] which used a modified Mahalanobis distance for each cluster which is iteratively adapted to fit ellipse-shaped clusters. The use of hyper-ellipses instead of hyper-spheres is more appropriate for AE clustering in presence of low density and high scattering. In the GK algorithm, the covariance between each pair of features is estimated so that possible redundancy or complementarity between features can be taken into account.

In this paper we propose a methodology to estimate the partition of AE data obtained in fatigue loading in presence of noise sources. The methodology includes an automated filtering step and a progressive feature selection. The algorithm proposed in [14] for quasi-static tests is adapted to be applied on fatigue tests. The next section is dedicated to presentation of the proposed methodology.

1. UNSUPERVISED PATTERN RECOGNITION METHODOLOGY

The flow chart of the methodology is shown on Figure 1.

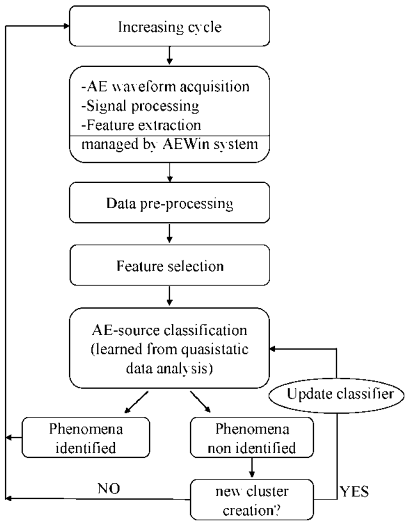


Figure 1: Unsupervised damage detection methodology

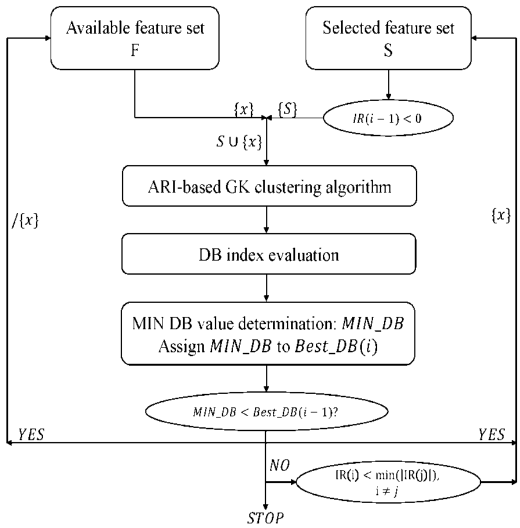


Figure 2: Progressive feature selection diagram

1.1 AE fatigue data pre-processing

- **Signal screening** : Continuous background noise due to hydraulic flows is essentially eliminated from the AE signal by a floating signal threshold, which is adjusted at a 40 dB level.
- **Noise-model-based filtering** : Based on the assumption that there is no damage during the setting-in-place time, a noise model is built using multivariate statistical test based on the Mahalanobis distance as used in novelty detection [15]. This model is then used to filter out AE events during the test which have the same characteristics as the modeled noise.

1.2 Progressive selection algorithm of AE features

The goal of this section is to propose an automated technique to detect relevant feature subsets for clustering of AE events. In contrast to feature reduction procedures (e.g. based on correlation dendrogram in [1]) or exhaustive search of global optimal feature combinations in [10], the principle of the presented approach is to combine gradually each feature from an available feature space with an initial feature subset. The feature selection is achieved by minimizing the value of Davies and Bouldin (DB) index [16] presented on Equation (1) :

$$DB = \frac{1}{k}\sum_{i=1}^{k} \max_{i\neq j}\left\{\frac{d_i + d_j}{D_{ij}}\right\} \tag{1}$$

where d_i and d_j are the average within-class distances of clusters i and j respectively, and D_{ij} denotes the distance between the two clusters i and j. This clustering validity index has been used by several authors in order to select optimal cluster number [9] or to evaluate feature subset partition [10]. Due to the way it is defined, as a function of the ratio of the within cluster scatter and the between-cluster separation, a lower value of this criterion means a good compactness and a good separation of dataset partition. The Figure 2 shows the diagram of the proposed algorithm based on a feature filtering approach [17]. Considering an initial selected feature set denoted S (empty by default), the algorithm will take each of available features from F to create a new subset with S. This subset is then partitioned by the clustering algorithm proposed in [14]. At the k^{th} iteration, a feature $f_i \in F$ is added to the current subset of features S_k, and the DB index DB_i of the partition obtained by the GK algorithm is computed. The subset of features S_{k+1} for the next iteration is given by $S_k \cup f_{i^*}$ with $i^* = \arg\min_i DB_i$ and the partition is then evaluated by the DB criterion. The additional feature of subset that minimizes the value of DB index is selected as the relevant one. Thus, this feature will be removed from F to S. At each iteration, the procedure generates k new subsets if the number of features remaining in F is k, because each new subset contains the features from S plus a new one taken from the remaining ones in F. The algorithm stops when no new subsets can improve the DB criterion. For each iteration i, an improvement rate is calculated by Equation (2) :

$$IR(i) = \frac{DB(S_i) - DB(S_{i-1})}{DB(S_{i-1})} \tag{2}$$

where $IR(i)$ is the improvement rate in the i^{th} iteration, $DB(S_i)$ and $DB(S_{i-1})$ are value of DB index of the best feature selection for the i^{th} and $(i-1)^{th}$ iteration. The sign of IR indicates if the DB criterion is improved (negative) or not (positive). In the last iteration j, *i.e.* $IR(j) > 0$, if $IR(j) < min_{i \neq j}|IR(i)|$ then the best-DB-index feature can be added to S to establish the final selected feature set.

1.3 AE source classification

Quasi-static tests are first applied to obtain a relatively low amount of data compared to fatigue by assuming that damage sources are similar from quasi-static to fatigue. The GK algorithm as proposed in [14] is applied to estimate the parameters of a given set of k clusters. An additional $k+1^{th}$ cluster is estimated during fatigue to include all feature vectors located far from the previous k clusters. The average Mahalanobis-like distance (used in GK) in each cluster representing its radius is estimated after the quasi-static data partitioning. A feature vector obtained during fatigue belongs to the $k+1^{th}$ cluster if its distance to nearest cluster is above the corresponding radius. Figure 3 resumes the developed procedure used for AE data analysis, showing its main steps.

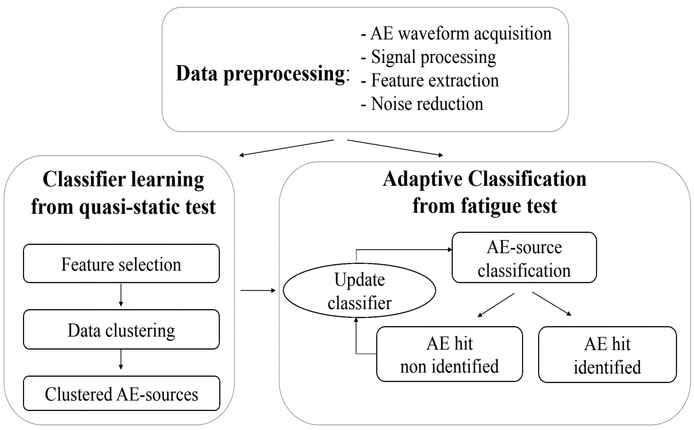
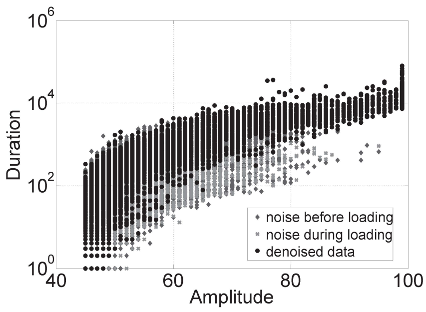


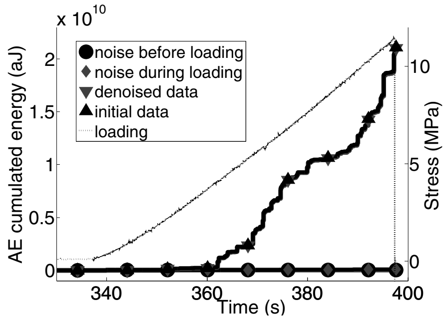
Figure 3: AE data analysis flow chart

2. EXPERIMENTATION

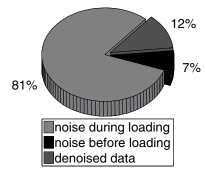
In this paper, health was assessed on composite split disks when subjected to quasi-static and cyclic fatigue loading up to failure. For quasi-static tests, a constant loading rate of 0.3 kN.s^{-1} was applied. For cyclic fatigue tests, a tensile/tensile sinusoidal loading with constant amplitude and frequency of 3 Hz was used. The tests were performed according to ASTM D2290 ”Apparent hoop tensile strength of plastic or reinforced plastic pipe by split disk method”. Rings were produced by cutting and machining filament-wound carbon fiber reinforced epoxy tubular structures intended for the manufacturing of flywheel rotors with a $[(90°)_2 \ / \pm 45° \ / \ (90°)_2]$ lay-up configuration. The transient elastic waves



(a)



(b)



(c)

Figure 4: Quasi-static dataset A1: (a) Duration vs. Amplitude; (b) AE cumulated energy; (c) Percentage in terms of population

were recorded during test at the material surface using a multi-channels data acquisition system from EPA (Euro Physical Acoustics) corporation (MISTRAS Group). The system is made up of miniature piezoelectric sensors (micro-80) with a range of resonance of 250 - 325 kHz, preamplifiers with a gain of 40dB and a 20 - 1000 kHz filter, a PCI card with a sampling rate of 1MHz and the AEWin software. The sensors were coupled on the specimen faces using silicon grease. The calibration of the system was performed after installation of the transducers on the specimen and before each test using a pencil lead break procedure. A part of the ambient noise was filtered using a threshold of 40dB. The acquisition parameters: PDT (Peak Definition Time) = 60 μsec; HDT (Hit Definition Time) = 120 μsec and HLT (Hit Lock Time) = 300 μsec were identified using preliminary measurements. Many features such as absolute energy, counts, hits, amplitude, duration, frequency centroid were calculated from recorded waves.

3. RESULTS AND DISCUSSION

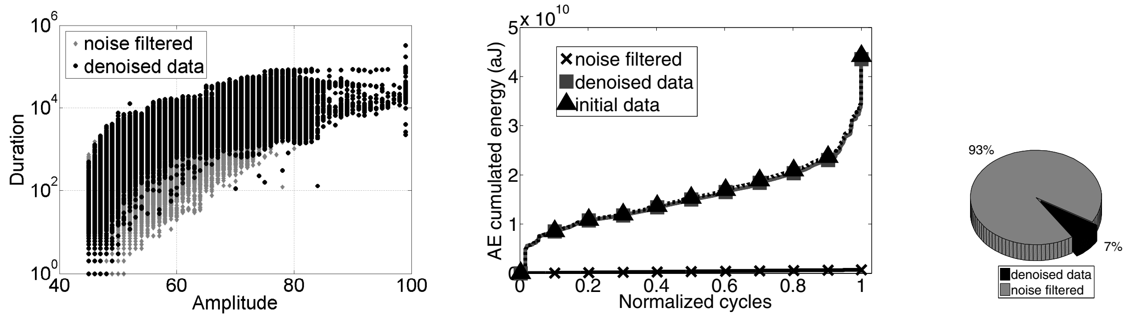
Two AE datasets A1 and A2 recorded during quasi-static and fatigue tests respectively are now used to present the proposed methodology.

3.1 Noise reduction

Noise modeling has been made from AE data recorded before application of load, *i.e.* during the first 320s of quasi-static test. Noise during loading is then filtered by this model. Figure 4(a) represents the whole A1 dataset made of 52,832 AE hits, in the duration-amplitude space, segmented into three populations: noise before loading, noise during loading and denoised data after application of noise model. The two first populations possess the same characteristics, the same location and the same scattering. This observation is justified by the graphic of AE cumulated energy on Figure 4(b). Indeed, the level of AE cumulated energy of noise before and during loading is negligible and the total energy is conserved within denoised data while the latter occupies only 12% of the whole dataset in terms of quantity (Figure 4(c)). Application of the noise model to fatigue dataset A2 made of 1,682,434 AE hits leads to the similar separation between noise and denoised data (Figure 5(a)). In spite of 93% of AE hits recorded associated to noise (Figure 5(c)), this highest population represents negligible AE cumulated energy level in comparison with that of denoised data (Figure 5(b)).

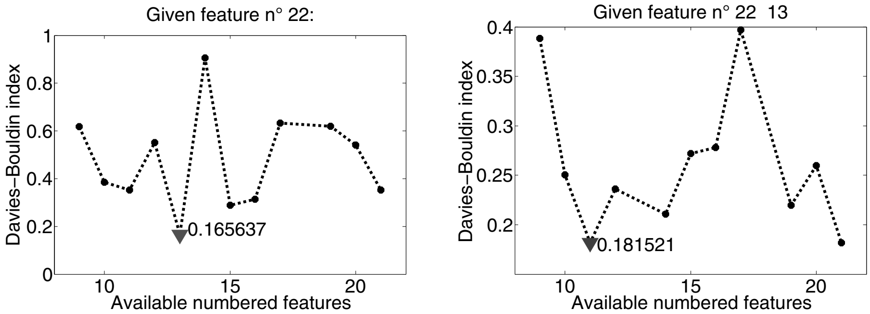
3.2 Feature selection

Many energy-based approaches of damage characterization or identification have been studied since AE energy provides a good correlation with damage mechanisms. Thus, in this work, absolute energy numbered by n°22 (Figure 6) is used to initialize the subset of relevant features. As the number of clusters is unknown, 3 cases were addressed to verify the stability of the selection algorithm by considering 4, 5 and 6 clusters. Applying the latter to quasi-static dataset A1 with 4 clusters, at



(a) (b) (c)

Figure 5: Fatigue dataset A2: (a) Duration vs. Amplitude; (b) AE cumulated energy; (c) Percentage in terms of population



(a) (b)

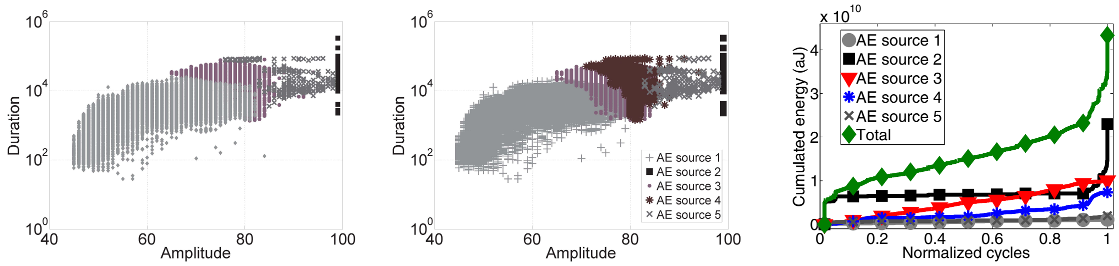
Figure 6: Case of 4 clusters: (a) first selection giving feature n°13 as the best; (b) second selection giving feature n°11 as the best

the first selection given energy-feature, the optimal DB index is given by the combination with n°13 corresponding to amplitude (Figure 6(a)). At the second selection given energy and amplitude features, the best score was obtained by the combination with n°11 corresponding to MARSE (Figure 6(b)). No more improvement of DB index is made by the next selection, so the algorithm is stopped by selecting the subset made of n°22, 13 and 11 as the most representative AE features. The same selection result was obtained with 5 and 6 clusters. In what follows, 4 clusters will be used as initial number of AE sources.

3.3 AE source detection

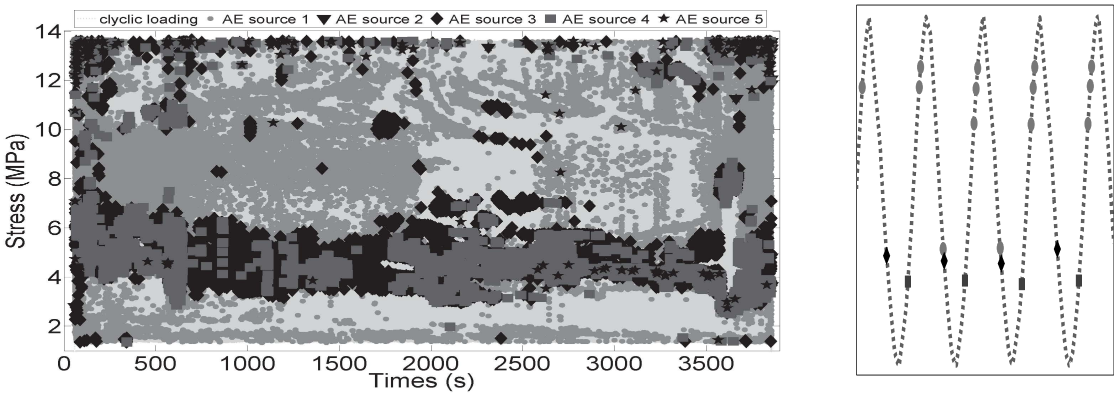
The denoised and selected feature subset in previous sections is now used to estimate the parameters of the clusters in quasi-static dataset A1 using the GK clustering algorithm proposed in [14]. Afterwards, testing directly this classifier with fatigue dataset A2 does not carry out a good separation (Figure 7(a)). In fact, overlapping zones between clusters can be observed due to a new AE source that did not exist in the case of quasi-static testing. Consequently, according to this hypothesis, by creating a new class, a better segmentation is obtained (Figure 7(b)).

In Figure 7(b), amplitude range of 5 detected AE-sources is clearly different. This can be explained by the evolution of AE cumulated energy of each source (Figure 7(c)). Despite its smallest population, AE source 2 is dominant in term of energy at the end of test. It could be associated to severe damage mechanisms such as fiber rupture, fiber bundle rupture, fiber pullout. AE source 1 is the most scattered and populated but represents negligible contribution energy to the total one. It could be friction between the specimen and the testing devices or very small cracks of matrix. AE source 5 generates long duration and high energy events that seem to be macro-matrix cracking or damage related to interfaces. It has been also observed in the Figure 8(a) that during the first 600s appears



(a) (b) (c)

Figure 7: Testing phase: (a) direct classification without adaptation; (b) adaptive classification giving better separation; (c) evolution of AE cumulated energy of each AE source



(a) (b)

Figure 8: Visualization of classified AE events during cyclic loading: (a) whole test; (b) snapshot of cyclic loading

an high concentration of AE hits including all modes, followed by a steady state where all activities due to damage slow down. This stage corresponds to accommodation phase of composite material subjected to fatigue loading. Again, until 3500s, an acceleration and accumulation of high energy AE hits occurs up to the ruine of the specimen. Concerning AE sources 3 and 4, they have an interesting interpretation: according to their apparition following loading and unloading, a repetitive phenomenon takes place all along of the test that AE source 4 locates mainly in loading phase and AE source 3 in unloading phase (Figure 8(b)). The latter could correspond to internal friction or fretting between the faces of the previously developed matrix cracks that could be associated to AE source 4. Again, this dissimilarity justifies the good capacity of cluster detection approach presented in this paper.

CONCLUSION

An unsupervised pattern recognition approach for AE data originating from fatigue tests on polymer-composite materials has been presented to tackle different existing challenges of AE analysis and damage detection: 1) data pre-processing, especially noise reduction; 2) automatic and fast feature selection; 3) clustering of big data from fatigue tests with cluster adaptation. The proposed methodology permits to overcome problems related to computing approaches involving time consuming, computational cost and accuracy gain. The first results on real fatigue tests demonstrate that the proposed methodology allows to identify some relevant clusters in loading and unloading phases, some clusters of different levels of energy which seems important for structural health monitoring.

ACKNOWLEDGMENT

This work has been carried out in the framework of the Laboratory of Excellence ACTION through the program "Investments for the future" managed by the National Agency for Research (references ANR-11-LABX-01-01).

REFERENCES

[1] A. A. Anastassopoulos and T. P. Philippidis. Clustering methodology for the evaluation of acoustic emission from composites. In *Journal of acoustic emission*, volume 13, pages 11–22. Acoustic Emission Group, 1995.

[2] Mikael Johnson. Waveform based clustering and classification of AE transients in composite laminates using principal component analysis. *NDT & E International*, 35(6):367–376, September 2002. 00040.

[3] J. Henry, Z. Aboura, K. Khellil, and S. Otin. Suivi de lendommagement en fatigue dun composite renfort interlock carbone/poxy par mission acoustique. *Matriaux & Techniques*, 100(6-7):643–652, August 2012.

[4] Jianguo P. Yu, Paul Ziehl, and Adrian Pollock. Signal identification in acoustic emission monitoring of fatigue cracking in steel bridges. pages 83471Z–83471Z, 2012.

[5] Jianguo Yu, Paul Ziehl, Boris Zarate, Juan Caicedo, Lingyu Yu, Victor Giurgiutiu, Brian Metrovich, and Fabio Matta. Quantification of fatigue cracking in CT specimens with passive and active piezoelectric sensing. volume 7649, pages 76490R–76490R–12, 2010.

[6] L. Calabrese, G. Campanella, and E. Proverbio. Noise removal by cluster analysis after long time AE corrosion monitoring of steel reinforcement in concrete. *Construction and Building Materials*, 34:362–371, 2012.

[7] N Godin, S Huguet, R Gaertner, and L Salmon. Clustering of acoustic emission signals collected during tensile tests on unidirectional glass/polyester composite using supervised and unsupervised classifiers. *NDT & E International*, 37(4):253–264, 2004.

[8] R. Gutkin, C.J. Green, S. Vangrattanachai, S.T. Pinho, P. Robinson, and P.T. Curtis. On acoustic emission for failure investigation in CFRP: pattern recognition and peak frequency analyses. *Mechanical Systems and Signal Processing*, 25(4):1393–1407, 2011.

[9] M. Moevus, N. Godin, M. RMili, D. Rouby, P. Reynaud, G. Fantozzi, and G. Farizy. Analysis of damage mechanisms and associated acoustic emission in two SiCf/[SiBC] composites exhibiting different tensile behaviours. part II: unsupervised acoustic emission data clustering. *Composites Science and Technology*, 68(6):1258–1265, 2008.

[10] M.G.R. Sause, A. Gribov, A.R. Unwin, and S. Horn. Pattern recognition approach to identify natural clusters of acoustic emission signals. *Pattern Recognition Letters*, 33(1):17–23, January 2012.

[11] Maria Halkidi, Yannis Batistakis, and Michalis Vazirgiannis. On clustering validation techniques. *J. Intell. Inf. Syst.*, 17(2-3):107145, 2001. 01273.

[12] Chris Ding and Xiaofeng He. K-means clustering via principal component analysis. In *Proceedings of the Twenty-first International Conference on Machine Learning*, ICML '04, page 29, New York, NY, USA, 2004. ACM. 00544.

[13] D.E. Gustafson and W.C. Kessel. Fuzzy clustering with a fuzzy covariance matrix. In *1978 IEEE Conference on Decision and Control including the 17th Symposium on Adaptive Processes*, volume 17, pages 761–766, 1978.

[14] Vincent Placet, Emmanuel Ramasso, Lamine Boubakar, and Noureddine Zerhouni. Online segmentation of acoustic emission data streams for detection of damages in composite structures in unconstrained environments. In *ICOSSAR 2013*, New York, NY, 2013.

[15] Charles R. Farrar and Keith Worden. Unsupervised learning novelty detection. In *Structural Health Monitoring*, pages 321–360. John Wiley & Sons, Ltd, 2012.

[16] David L. Davies and Donald W. Bouldin. A cluster separation measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-1(2):224 –227, April 1979.

[17] George H. John, Ron Kohavi, and Karl Pfleger. Irrelevant features and the subset selection problem. In *Machine Learning: Proceedings of The Eleventh International*, pages 121–129. Morgan Kaufmann, 1994.